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Team 3: Data Farming the Agent-Based ELICIT (abELICIT) Model

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Team 3: Data Farming the Agent-Based ELICIT (abELICIT) Model

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INTRODUCTION

ELICIT (Experimental Laboratory for the Investigation of Collaboration, Information-sharing and Trust) is a research and experimentation program developed for the US DOD CCRP (Command and Control Research Program) to conduct research related with collaboration, information sharing and trust in organizations. The ELICIT platform is an experimentation environment supported by software tools and procedures that allows instantiating different C2 approaches and observation of behaviors and dynamics in the information, cognitive and social domains. Agent-based ELICIT (abELICIT) is the agent-based functionality of the ELICIT platform, and allows a researcher to conduct human-only, agent-only or hybrid human and agent experiments. The version used in this workshop was version 2.4; we focused on running experiments using software agents only.

To explore the vast input space of the abELICIT model and understand how changes in the input variables affect various output metrics, e.g., how shared awareness affects agility of a C2 approach, the CCRP ELICIT team and the international ELICIT CoI (Community of Interest) will benefit from an automated data farming capability within the ELICIT platform. Toward that end, the abELICIT data farming team first conducted an experiment aimed at understanding the ordering effects of "factoids", i.e., when specific information reaches agents, and how that might impact several metrics of interest. Additionally, we were interested in observing how ordering of the factoids makes a difference while agent parameters are systematically varied, as well as looking at different kinds of ordering, based on the types and impacts of the factoids.

Initially, our goals during the workshop were to continue analysis of the initial experiment, identify a set of possible next steps, to learn and understand a little more of what abELICIT is and how it is used by the ELICIT CoI, and where our work can positively impact the community. We set aside the original goal of continuing the analysis of the initial experiment and instead set an additional goal to conduct a simple exploratory data farming experiment using abELICIT. This would allow us to demonstrate proof-of-concept and to get a feel for the necessary mechanics in setting up and conducting a data farming experiment with abELICIT, as well as continuing to learn more about abELICIT functionality.

We next give an overview of abELICIT functionality. Following that is a description of our data farming experiment, a note on the illustrative results and analysis, and a summary concludes the paper.

abELICIT Overview

Within an abELICIT experiment (also applies to an ELICIT experiment), the problem the agents need to solve is collectively determining the where, what, when, and who of a future, fictitious terrorist attack. Information on this attack is contained in a set of "factoids", with each factoid containing information relevant to one aspect of the attack. To whom and when the factoids are distributed to the agents is a function of the individual experiment. The agents then process the factoids received to determine, among other things, whether to share that information with other agents it is connected to, or to post or pull factoids from a notional website dedicated to a particular aspect of the problem. For abELICIT, whether and when the agents have solved the problem is determined by processing the log files after the run is completed.

Software agents may be parameterized according to 54 parameters that determine, among other aspects, the way they process information, build awareness, socialize and identify, as illustrated in Figure 1. Whether to share, how often to share, and the likelihood to seek information are all examples of agent parameters that can be varied. A number of parameters are associated with the amount of time a particular action takes, e.g., how long it takes to share or post a factoid once the agent determines it will share or post. Finally, there are a few Boolean (on/off, true/false) parameters such as whether the agent is a guesser or a hoarder of factoids.

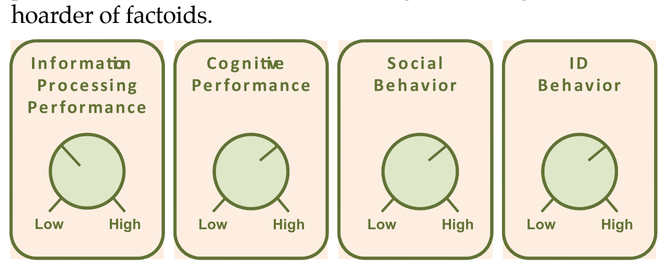

Figure 1: Parameterizing Agent Characteristics

For more detailed information about abELICIT, refer to (Ruddy 2009, Ruddy 2010).

Experiments

To gain familiarity with abELICIT, help design our initial experiment, and determine a small subset of the parameters to focus on, the team went through each of the 54 agent parameters, categorized them into the four broad categories depicted in Figure 1, and then prioritized them according to how we thought they may impact performance. We decided to focus on 7 parameters to characterize two types of agent behaviors, and used those in conjunction the two available organizational structures of HIERARCHY and EDGE (provided as examples on the ELICIT server). These 7 parameters were: postedTypes, sharedTypes, propensityToShare, shareWith, shareWithWebSites, propensityToSeek, and primary area of interest (more details on all the parameters can be found in Ruddy 2010).

The experiments were designed to test performance of (a) Traditional HIERARCHY and (b) EDGE organizations when their constituent members are either: (i) TYPE 1: highly specialized (task focused), share/post sporadically and strictly within hierarchical chain; or (ii) TYPE-2: flexible across tasks, share/post, share/post often and across all members. (More information on differing C2 approaches and Hierarchy and Edge organizations can be found in, e.g., Alberts 2003 and Alberts 2006).

The four possible combinations of two organizational structures (HIERARCHY and EDGE) with two agent behaviors (TYPE 1 and TYPE 2) resulted in the 2x2 design of experiments matrix presented in Table 1. Hierarchy 1 (H-1) and Edge 1 (E-1) are the "usual" Hierarchy and Edge organizational structures, with Hierarchy 2 (H-2) and Edge 2 (E-2) being hybrid structures.

Agent Behavior

Organizational Structure		
	Hierarchy 1 Agent Behavior 1: •Specialized per working space (who, what, when, where) •Share/post within team •Including team leader and cross team coordinator	**Hierarchy 2** Agent Behavior 2: •Flexible working space (who, what, when, where) •Share/post with all agents
	Edge 2 Agent Behavior 1: •Specialized per working space (who, what, when, where) •Share/post within team •Including team leader and cross team coordinator	**Edge 1** Agent Behavior 2: •Flexible working space (who, what, when, where) •Share/post with all agents

Table 1: Design of Experiments

Four runs, one run for each of the combinations (designs) above, were conducted, comprising a total of 68 agents (17 agents per run) and 2 organizational configuration files. We first created a spreadsheet that listed the 68 agents with their settings for the 7 agent parameters, keeping the other 47 agent parameters fixed. We then created a script (in the computer language R) to generate the 68 agent files, combined that with the organizational files and other supporting files for an abELICIT run, and submitted the runs to the ELICIT server. After the runs were completed, we downloaded the ELICIT log files and post-processed them to extract the data.

Results and Analysis

Unfortunately, and perhaps not surprisingly given our crude settings, the results obtained were not within valid ranges. For example, organizational effectiveness could not be determined since agents didn't provided identifies. TYPE-2 agents did an enormous number of shares (a total of 13328 - we assumed it was a consequence of setting the 'propensityToShare' parameters) and no pull actions. The fact that TYPE-1 agents in the hierarchy didn't perform post actions is also a matter that needs investigating. Agents also displayed a consistent and highly symmetrical behavior (e.g., same number of shares sent and received).

The lack of validity for this data set was likely due to the team's inexperience with abELICIT, the specific selection of agent parameters to vary and their ranges, and the setting of the other, fixed agent parameters. However, our main goal for this workshop was one of understanding the data farming mechanics for abELICIT and not a focus on any particular results, and we believe we succeeded in that goal. It is clear, though, that it is crucial in future work to determine adequate ranges of agents' parameters and their interaction with other agent characteristics (Figure 1) so that runs yield valid results. Nonetheless, a deeper look into these particular results and why the results were outside seemingly valid ranges might prove useful.

Nevertheless, to further explore the data and the types of analyses that could be obtained, we looked at three sociograms that provide a visualization of the social-networks generated by these illustrative experiments: Traditional Hierarchy with TYPE-1 agents (Figure 2), EDGE with TYPE-2 agents (Figure 3) and EDGE with TYPE-1 agents (Figure 4). These and other tools, applied to data from experiments across a wider range of allowable configurations, could provide great insight into which of the agents' parameters, and their interactions, have the most effect on outcome metrics. [Note: post-processing of the data and the construction of these graphs were graciously made by Marco Manso and the set of tools he previously developed to examine ELICIT output (Manso and B. Manso, 2010) and (Manso and M. Manso, 2010).]

In the figures below, the yellow nodes are the websites (WHO, WHAT, WHEN and WHERE), and the other colored nodes are the agents (different colors represent the roles in the organization, and the node labels reflect notional names for the agents). The edges or lines between the nodes represent connectivity between the nodes, and the width of the edge indicates the amount of sharing of factoids (with other connected agents) or the posting or pushing of factoids (with websites).

Figure 2 is a traditional HIERARCHY with TYPE-1 agents (the H-1 setting described above). The red colored nodes are team members, the purple colored nodes are team leaders, and the aqua colored node is the Cross-team coordinator. Team member, Team leader, and Cross-team coordinator are specific agent roles in ELICIT and abELICIT. In this case, there are some links that are missing, e.g., there should be links connecting Sam-WHERE and Sidney-WHERE, and similarly for the WHEN node. There also appears to be more connections between agents than we might expect for the HIERARCHY organization. This type of visualization is beneficial for easily discovering these types of anomalies.

On the other hand, trying to make sense of the connections in Figure 3 would be challenging. In this case, corresponding to E-1 setting above, all agents are linked to all websites and each other, illustrating a fully connected network.

Finally, in Figure 4, we have a hybrid structure, corresponding to the E-2 setting above, which uses an EDGE organizational structure with HIERARCHICAL agent behaviors. Again, more work would need to be done in order to determine the implications of these differing structures and to explain these particular outcomes.

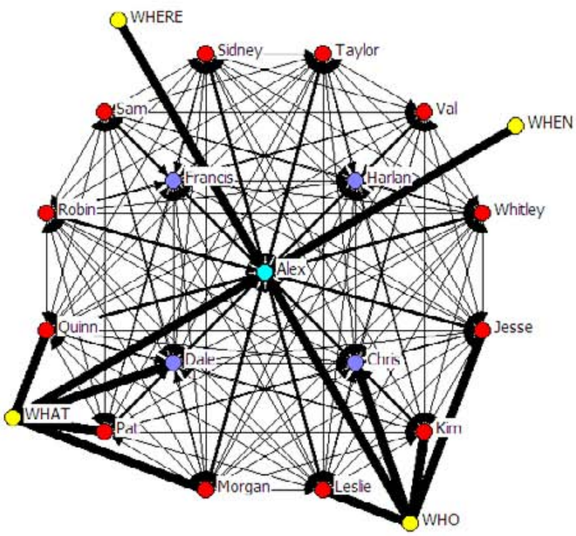

Figure 2: Traditional Hierarchy with TYPE-1 agents

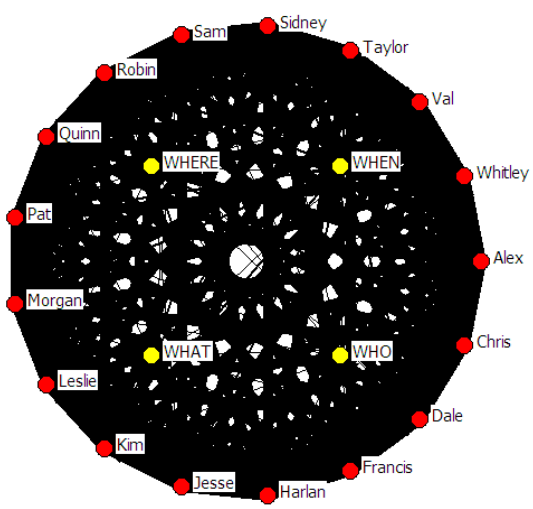

Figure 3: EDGE with TYPE-2 agents

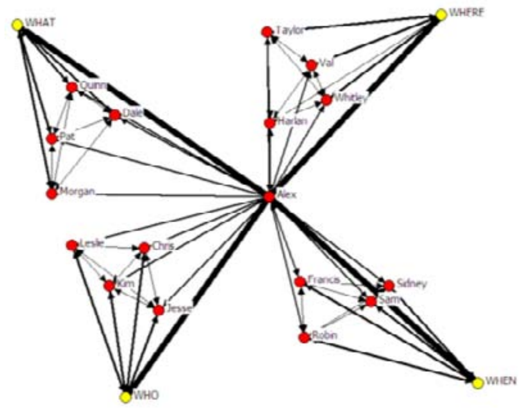

Figure 4: EDGE with TYPE-1 agents

SUMMARY

During IDFW 21, the abELICIT team (Team 3) learned more about the ELICIT platform and the agent-based functionality in abELICIT. Starting with an overall introduction of ELICIT and abELICIT, the team then proceeded to prioritize the 54 agent configuration parameters, ranking the parameters based on their expected influence on several outcome measures. We discussed a first data farming experiment using a 22 full-factorial design (4 runs), comparing a classic C2 hierarchy and an edge organization, and hybrids of those. This experiment was used to illustrate the data farming process and as a means to become familiar with the mechanics of making an abELICIT batch run. We then constructed 68 agent configuration files (17 agents * 4 runs) and an agent batch file and submitted those runs through the ELICIT server. We downloaded the data and began the analysis of that data by workshop end.

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